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Maximizing Economic Host Capacity Related to Distributed Generation, and Improving the Power System Performance

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ABSTRACT: There are numbers of technical limitations that must to be satisfied for the operation of the power systems, and these limitations are related to the power flow of the power system, thus the solar panels cannot inject any unlimited amount of power into the power system. Therefore, the maximum injection power of solar panels is limited to the specific value. This issue is also true for the reactive power produced or consumed by SVCs and solar panels, so the maximum injected power of photovoltaic panels must be obtained in such a way that the technical limitations of the power system are maintained. In the current research, a 33 bus radial distribution network has been considered and the goal is to maximize the injection power of photovoltaic panels, minimize the network power losses, by reconfiguring in this type of the network and establishing effective coordination between the control devices, including the output reactive power of photovoltaic panels and the fire angle of the SVC and graph of the power system. The bus voltage should be within the allowed range, and the cost of purchasing electricity from the upstream network should be minimized. The results of the simulation on the 33 bus radial network confirm the validity of the above claims.

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1- Introduction

Nowadays, the optimal operation of power systems, which all the technical constraints of the system are within the allowed range, has become a challenging issue. The nature of power systems is dynamic, and system variables, such as buses voltages and currents are constantly changing. On the other hand, the loading of the power system and the output power of distributed generation also have uncertainties, and these issues threat the security of power system. Since there are constant changes in power system loading, the first variable which fluctuates is the bus voltage, and therefore line current and line losses are also affected. Today, the main goal of most power system operators is to minimize the cost of purchasing electricity from upstream network, and generating electricity by taking into account all the technical constraints of the power system and the uncertainties of system loading. Since the electricity generation in power plants require fuel consumption, which in turn pollutes the environment and reduces fossil fuel sources, the best way is to use the distributed generation in the power system. These sources include solar panels and wind farms. However, as mentioned, these sources are uncertain and this issue endangers the security of the power system and system loads.

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1- 1- Research Literature

In [1], using Monte Carlo power flow algorithm, the goal is to calculate the maximum host capacity in a low voltage distribution system, and different modes are considered to take into account the uncertainties. Reference [2] uses a probabilistic method to calculate the maximum host capacity for distributed generation resources, and this methods are considered as an effective method for calculating uncertainties in island networks compared to the Monte Carlo technique. In [3], mixed nonlinear optimization models are used to improve the maximum host capacity related to the distributed generation in the distribution network and using the genetic algorithms. However, other intelligent algorithms have difficulty finding the optimal solution. In addition, with the development of active distribution network management methods, researchers have turned their attention to improving the host capacity of distributed generation by using different methods of active distribution network management. In reference [4], the method of calculating the host capacity related to the distributed generation is included by including reconfiguration and On-Load Tap Changer (OLTC) and reactive power compensation. Reference [5] presents a robust optimization model for managing distribution network-based SOPs (Soft Open Points), and this networks include distributed generation. Reference [6] presents a report that the use of SOP in distribution networks reduces the negative effects of distributed generation and thus increases the host capacity in the distribution network. References [7, 8] provide a two-level model for electric vehicles in distribution networks, including solar panels, which can increase host capacity in this type of network. In [9], the aim is to minimize the voltage deviation by performing reconfiguration in the radial distribution network, considering the OLTC, and capacitive banks in the network. In general, optimization approaches are based on derivatives but many modern optimization methods are tricks without considering derivatives, which population-based methods are very popular. These methods include well-known genetic algorithms that are inspired by the process of evolution in nature, differential evolution, the search for coordination, and the particle swarm optimization method [10-13]. Population-based methods generally produce initial solution candidate vectors, and by using operators such as intersection or mutation, better and newer solution candidate vectors are produced. The recently introduced optimization method is inspired by the gray wolf hunting process. In this method, the numerical results of several optimization index functions, which are in fact a combination of single-value, multi-value, multi-value fixed-dimension, and composite functions are compared. Classical engineering optimization problems such as stress/compression spring design, pressure tank design, and welded rod design have been compared with other exploratory methods [14]. Based on the numerical results, the gray wolf optimization method works better than other exploratory methods, such as particle swarm optimization, differential evolution, and genetic algorithm. This method has better objective function values and is used to solve engineering problems. The binary version of the Gray Wolf optimization algorithm is used to search problems in optimal selection [15]. Reference [16] examines optimization methods in which the derivative is not applicable. References [17, 18] also introduce the optimization methods that have used derivatives. In general, these methods are based on nonlinear problems or solve the optimization problem by using weight coefficients. Population-based methods are very useful for distribution systems. The method of the gray wolf optimization algorithm is optimally used to receive the maximum power point in systems with solar panels [19, 20]. In [21], using DGs reduce carbon emissions, improves power quality, and reduces power losses, therefore finding the optimal location and size of the wind turbines is an important issue. In this research, the aim is to find the optimal location and size of the wind turbines in a 69-bus radial network by using the gray wolf optimization algorithm. In [22], the aim is to find the optimal size and location of DG in the power system. Improving the stability of the power system, improving the voltage profile, minimizing power losses, and the above items have been implemented on systems 33 and 69 radial bus. In [23], the purpose is to minimize power losses in lines, increase voltage stability, and reduce environmental pollution. The above-mentioned items have been tested on two systems, 30 and 57 bus, and the blue whale optimization algorithm has been used to minimize the target functions. The aim of [24] is to minimize the operating costs and voltage deviations of the power system. The above items have been tested on a standard 33-bus system. In [25], power systems with 69, 70, 119 and 136 buses have been tested and in the relevant simulations, the technical constraints of the system such as production and consumption balance and voltage and current limitations of the lines have been applied. In [26], the goal is to increase the maximum power capacity of the network and reduce the deviations of the network voltage simotaneously. The simulation was done on a standard 33-bus system. By using the genetic optimization algorithm, the optimal topology of the network has been obtained to achieve the above-mentioned goals, and it is clear that by performing the reconfiguration, the injected power of the network can be increased, and the voltage stability and reliability of the network can be increased at the same time, and the imbalance of the power demand and generation can be solved. In [27], the goal is to maximize the injected power of solar panels in the distribution network. Of course, the aforementioned goal can be achieved by reconfigurating of the distribution network. The mentioned experiment has been tested on a standard 33 bus radial network and the system loading is changing. The results show that the maximum injected power of the solar panels cannot exceed a certain limit due to the system voltage limitations and is actually limited, but by reconfiguration, the host capacity can be increased to its best state so that the system voltage limitations are also established.

Therefore, the innovation of the current article is the proof of the effect of changes and the coordination of control variables including the fire angle of SVCs and reactive power of solar panels and reconfiguration on improving the performance of the power system, which is studied for the first time.

2- Research Method

The negative effects of greenhouse gas emissions on the planet are clear to everyone. Therefore, the users of the power system are always looking for solution of this issue in order to provide the loading of the power system in such a way that the need to buy electricity from the upstream network is minimized. Therefore, the purchase price of electricity from the upstream network will be minimized. Distributed generation, such as solar panels or wind farms, are low-risk sources for the environment and for electricity generation. However, the output power of the solar panels is uncertain, which causes instability of the power system. The solution to these problems is that by reconfigurating the distribution network, considering the distributed generation, and power electronics, such as SVC, we can maximize the host capacity of solar panels in the power system at any amount of power system loading by obtaining the optimal network topology and appropriate values of reactive power of solar panels and SVC fire angle. Therefore, in addition to minimizing the purchase price of electricity from the upstream network, the emission of greenhouse gases from electricity generation in power plants will also be minimized, and we have also been able to minimize distribution network losses and voltage deviations of busbars.

3- Targeted Functions

To calculate the host capacity, Eq. (1) is used [9, 28].

$$HC = \sum_{i=1}^{n} P_{1i} \quad (1)$$

Where HC is the total injected power of solar panels to the grid and P_{1i} is the injected power of the i-th solar panel.

To calculate the cost of power received from the upstream network, Eq. (2) is used. It is clear that by reducing the amount of electricity purchased from the upstream network, the amount of host capacity increases.

$$F_1 = P \times k_b \times T \quad (2)$$

Where F_1 is the amount of power received from the upstream network that should be minimized, P is the amount of power received from the upstream network, K_b is the cost of purchasing electricity from upstream network, and T is the index of time.

To calculate the cost of power losses in the lines, Eq. (3) is used.

$$F_2 = Ploss \times k_e \times T \quad (3)$$

Where F_2 is the amount of line losses that should be minimized, $Ploss$ is the active power losses of the network, and K_e is the cost of losses which is 0.06 dollars per kilo Watt.

Eq. (4) is related to the maximization of host capacity cost.

$$F_3 = -1 \times (HC \times B_p) \times T \quad (4)$$

Where F_3 is the total injected power of solar panels that should be maximized, HC is the total injected power of solar panels to the grid, and B_p is the price of injected power of solar panels is 0.03 dollars per kilo Watt.

Eq. (5) is the objective function, as follows:

$$F = F_1 + F_2 + F_3 \quad (5)$$

Where F is the overall objective function

3- 1- Technical Limitations of the Power System

The forward-backward power flow is used for simulation. The following formulations are related to power flow constraints.

$$Q_{pv} = \sqrt{s^2 - P_{pv}^2} \quad (6)$$

Eq. (6) is related to the reactive power of solar panels.

Where, Q_{pv} is related to the reactive power of solar panels, P_{pv} is the active power of solar panels, and S_{pv} is the complex power of solar panels

The reactive power of the bus with SVC is calculated with Eq. (7), as follows:

$$Q_{isvc} = Q_{svc} - Q_{iload} \quad (7)$$

Where Q_{isvc} is the reactive power of bus with SVC, Q_{svc} is the reactive power of svc, and Q_{iload} is the reactive load power.

Eq. (8) is related to the active power of the buses with solar panels, as follows:

$$P_{ipv} = P_{pv} - P_{iload} \quad (8)$$

Where, P_{ipv} is the active power of the buses with solar panels, P_{iload} is the active power of the load of i-th bus, and P_{pv} is the active power of the solar panels

Eqs. (9) and (10) show the range of changes in the active and reactive powers of the solar panel, respectively.

$$P_{pv}^{\min} \le P_{pv} \le P_{pv}^{\max} \quad (9)$$

$$Q_{pv}^{\min} \le Q_{pv} \le Q_{pv}^{\max} \quad (10)$$

The acceptable range of the buses voltages is given in Eq. (11).

$$0.95 \le V_i \le 1.05 \quad (11)$$

The complex power of the solar panel, S_{pv}, is 120kVA. The acceptable range of the SVC fire angle ($ANGLE_{svc}$) and the DG active power (P_{g1}) are $90 \le ANGLE_{svc} \le 180$ and , $0 \le P_{g1} \le 120kw$ respectively.

3- 2- The Optimization Algorithm of the Grey Wolf

The gray wolf algorithm is based on the actual behavior of the gray wolves. This algorithm relies on their hunting process and social hierarchy. Socially, gray wolves live in groups of 5-12. They have social hierarchies, and the highest ranking member of this community is the alpha (a), which decides about the hunting, sleeping, and everything else. In the gray wolf hierarchy, the beta rank (b) is second. Beta is a candidate to become an alpha when they die or grow old. Beta helps alphas make decisions and commands. Lower-level wolves are named the delta. Deltas are the guardians. The lowest level of the wolf social hierarchy is omega. This algorithm finds the best solutions and labels them with ω, α, β in each iteration. Thus, the process of finding a solution consists of the siege, the hunting, the attack and the search. The first step is the bait siege, and the calculations of the vectors related to this step are shown in the following equations [14].

$$\vec{d}=\left|\vec{C}*\overline{X_p}(t)-\vec{X}(t)\right|$$
$$\vec{X}(t+1)=\overline{X_p}(t)-\vec{A}*\vec{d} \tag{12}$$

Where t represents the current iteration, $\vec{A}$ and $\overrightarrow{X_P}$ are the coefficient vectors $\overrightarrow{X_P}$ and $\vec{X}$ represent the prey and gray wolf position vectors. The coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated according to the following equation.

$$\vec{A}=2\vec{a}\vec{r_1}$$
$$\vec{C}=2\vec{r_2} \tag{13}$$

Where $\vec{r_1}$ and $\vec{r_2}$ there are random vectors that take values between 0 and 1 and the numerical values $\vec{a}$ decrease linearly from 2 to 0 during the iterations.

The second step is hunting. In each iteration, the position of the prey is predicted using distance information δ, α, β with the prey. The position of other elements is then updated based on these three better positions. This step is displayed in the form of Eq. (14).

$$\overrightarrow{D_\alpha}=\left|C_1X_\alpha-X\right|$$
$$\overrightarrow{D_\beta}=\left|C_2X_\beta-X\right|$$
$$\overrightarrow{D_\delta}=\left|C_3X_\delta-X\right|$$
$$X_1=X_\alpha-A_1D_\alpha$$
$$X_2=X_\beta-A_1D_\beta \tag{14}$$
$$X_3=X_\delta-A_1D_\delta$$
$$X_{t+1}=\frac{X_1+X_2+X_3}{3}$$

The next step is to attack the bait, which $\vec{a}$ is going to be reduced. Afterwards, $\vec{A}$ will also be reduced. When $\vec{A}$ is between -1 and 1, the wolves may attack. $\vec{A}$ is used for the targets of searching widely through the random values bigger than 1 and lower than -1.

The flowchart related to the gray wolf algorithm is shown in Fig. 1.

Fig. 2 shows the flow chart of simulation steps. 24 hours are considered and the simulation process starts at 1 am until we reach 24 pm. For 1 am, the number of wolves related to the gray wolf optimization algorithm and the number of iterations of the algorithm are set, then variables for the amount of reactive power output of solar panels, the number of tie switches that must be disabled, and the amount of power received from the upstream network are defined. Next, the renge of the changes of variables and the load of the power system in every hour is defined, the backward-foreward power flow is done and the voltage of the lines and the amount of line losses and the amount of host capacity, the amount of power received from the upstream network, the optimal topology of the power system, the svc fire angle, the reactive power output of the solar panels are determined, and these values are stored for 1 am. Afterwards, we repeat the same steps for 2 am and we continue these steps until we reach 24 pm, where the graph related to the amount of lines finally losses, and the amount of voltage buses, the amount of power received from the upstream network, and the amount

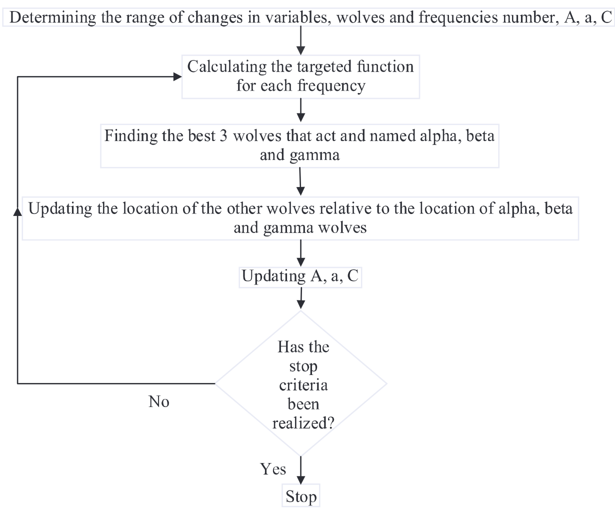

Fig. 1. GWO Algorithm Flowchart

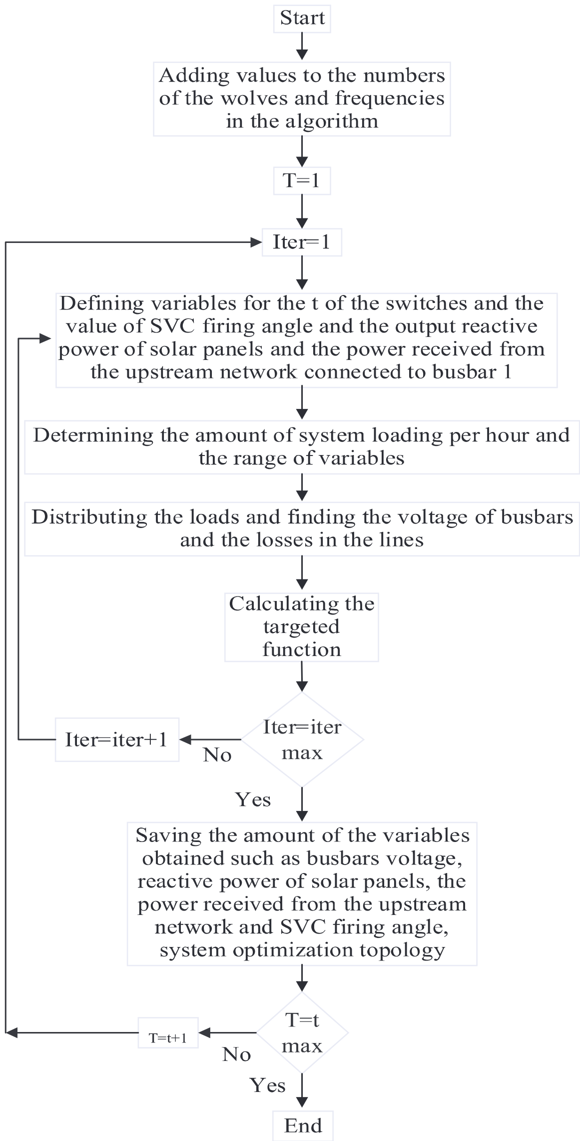

Fig. 2. the flowchart of performing simulation steps

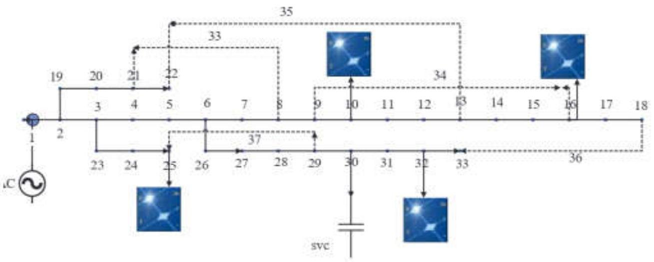

Fig. 3. The shape of the studied network in the presence of SVC and the solar panel, considering the coordination between the controlable devices [8]

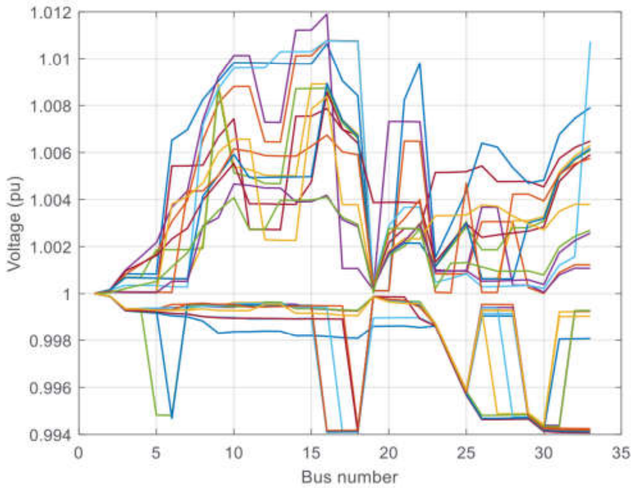

Fig. 4. System bus voltage after reconfiguration and coordination between control variables

of host capacity during 24 hours are drawn in the form of a diagram.

3- 3- Initialization

At this stage, the population size, maximum number of iterations, initial values C, a, and A are adjusted using Equation 14. The wolf population elements for the reactive power output of the solar panels network, the active power purchased from the upstream grid, the number of Tie switches, and the SVC fire angle for the Fig 3 network are initialized. After quantification, the unique sample is as follows;

$$individual = [Q_{pv1}, \ldots\ldots\ldots\ldots Q_{pv4} \quad P_{pv1}, \ldots\ldots\ldots\ldots P_{pv4} \quad P_{dg}, SW_1, \ldots\ldots\ldots\ldots SW_5, ANGLE_{svc}] \tag{15}$$

4- Simulation and Discussion

In this part, the simulation results are presented. A 33-bus distribution network is considered, and also the topology of the studied network is taken from reference 8, and the optimal placement of devices has led to the placement of devices such as solar panel and SVC in buses visible in the Fig. 3. Additionally, the amount of active power output of solar panels has been measured in real conditions and at different hours, and these values have been taken from reference 29. In this network, which is 33 busses and radial, 4 solar panels are installed in busses 10, 16, 25, and 32, respectively, and also one SVC is also installed in bus 30. This network is considered from 1:00 AM to 24:00 PM, and it is assumed that the amount of load on buses changes every hour and the goal is that by reconfiguration this type of distribution network and creating effective coordination between reactive power output of solar panels and SVC fire angle and optimal power system topology, minimize bus voltage deviations, minimize network losses, obtain optimal power system topology, minimize cost of purchasing electricity from the upstream network and maximize the injected power of solar panels (host capacity). Therefore, the cost of purchasing electricity for network subscribers will be reduced, as well as the emission of greenhouse gases due to the burning of fossil fuels for electricity production. It should be noted that, every hour the obtained results are drawn in the form of a graph. To achieve the aforementioned goals, MATLAB software, Gray Wolf, TLBO, and PSO optimization algorithms have been used for the optimization.

Table 1. Number of tie switches should be disconnected

Hour	The number of tie switches	Hour	The number of tie switches
1	5, 13,10, 27, and 17	13	5, 7, 35, 32, and 12
2	8, 13, 17, 5, and 28	14	37, 10, 18, 14, and 15
3	30, 13, 26, 7, and 9	15	7, 35, 10, 28, and 15
4	31, 14, 10, 5, and 28	16	27, 24, 6, 9, and 14
5	31, 11, 13, 4, and 6	17	14, 11, 5, 22, and 16
6	28, 18, 10, 35, and 15	18	5, 9, 7, 22, and 13
7	26, 10, 13, 22, and 5	19	19, 10, 23, 12, and 26
8	21, 20, 15, 34, and 5	20	13, 9, 27, 3, and 16
9	20, 28, 13, 11, and 36	21	25, 33, 13, 21, and 17
10	14, 8, 7, 9, and 27	22	12, 5, 6, 15, and 21
11	16, 11, 27, 19, and 13	23	28, 6, 10, 21, and 15
12	8, 9, 4, 27, and 13	24	30, 28, 13, 11, and 4

Table 1 shows the number of tie switches that must be deactivated every hour for the power system to obtain its proper topology. In fact, the number of tie switches are the same as the number of lines, and each line is electrically connected by a tie switch in the power system. It should be noted that the optimal topology of the system must have the condition of no ring and no island in order to maintain the radiality of the system. It is noteworthy that we considered 24 hours, and each hour was compared to the previous hour, the load of the power system changes slightly, so in each hour the topology of the power system must be obtained, which can be seen in Table 1.

As it can be seen from Fig. 4, after the reconfiguration and the coordination between the control variables, the deviations of the system voltage have been reduced. In addition, the buses voltages have also been within the permissible range. After coordination between the control variables, the bus voltages are lower than 1 perunit. The reason is that this part of Fig. 4 is related to the times when the sun has not yet risen, and therefore the solar panels cannot inject power into the

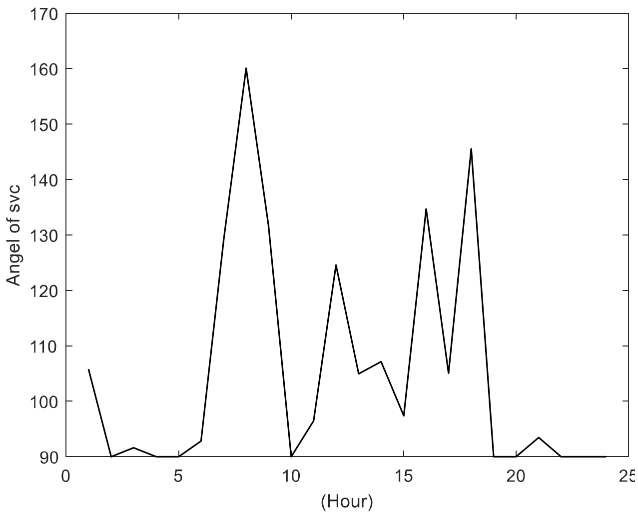

Fig. 5. Svc fire angle changes

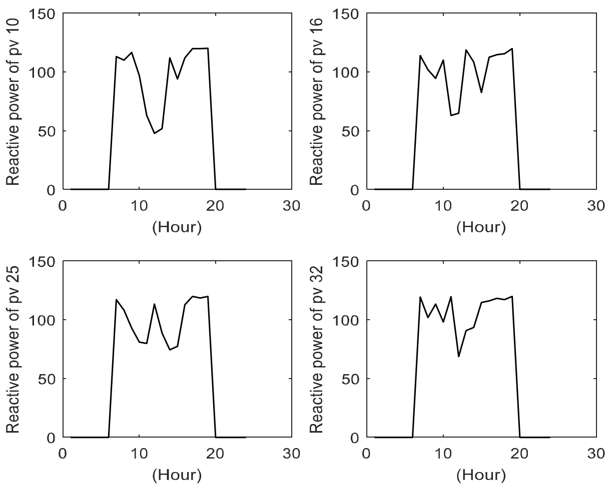

Fig. 6. The changes in the output reactive power of solar panels

system. However, it can be seen that the voltage of the buses is higher than 1 punit when the sun has risen and the solar panels can inject power. It should be noted that every hour the loading of the power system busbars change, so the voltage of 33 busbars will be different from the voltage of 33 busbars in the next hour, thus each colored line represents the voltage of these 33 busbars in a specific hour, and therefore we have 24 colored lines.

Fig. 5 shows the changes in SVC fire angle, resulting from the reconfiguration and coordination between the control variables in the network. According to the amount of system load changes, SVC fire angle also changes. In fact, according to the conditions we have created in the network and to improve the operation of the power system, we were able to minimize the amount of electricity purchased from the upstream network and the power losses of the lines, and at the same time maximized the injected power of the solar panels.

Fig. 6 shows the output reactive power of solar panels during 24 hours. Solar panels can only inject their power

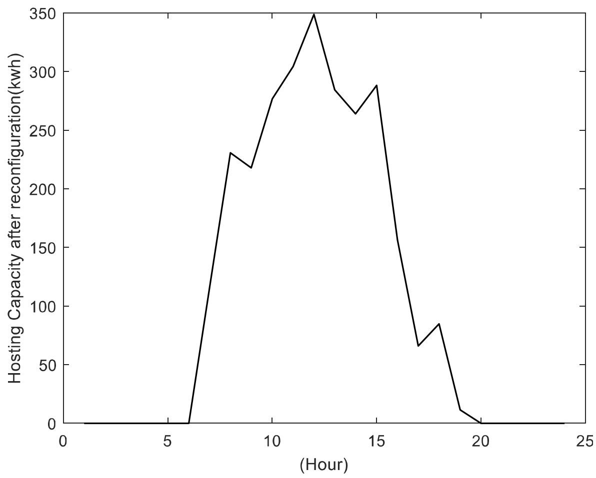

Fig. 7. The amount of host capacity changes related to solar panels

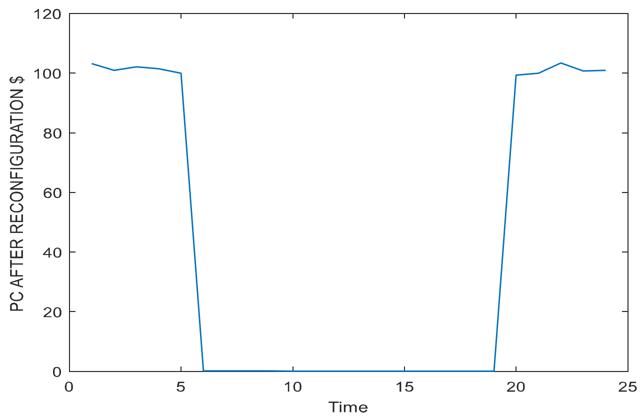

Fig. 8. The cost of purchasing electricity from the upstream network after the reconfiguration

when the sun is present in the sky. However, during hours such as 1 to 5 in the morning and 20 to 24, due to the fact that the sun is not present in the sky, the solar panels cannot inject power into the system. In fact, this amount of injected reactive power of the solar panels and the fire angle of the SVC described in Fig. 5 should be created in different loadings in the system in order to improve the performance of the power system, since the used solar panels have an inverter and this helps us in adjusting the output reactive power of the solar panels.

Fig. 7 shows the amount of host capacity changes after reconfiguration and coordination between control variables. Solar panels can only inject their power when the sun is present in the sky. It is also clear that the panels cannot inject power into the system only between the hours of 1 to 5 and 20 and 24, because the sun is not present in the sky during these hours. It can also be seen that the maximum host capacity has reached about 350 kilowatts after the reconfiguration and effective coordination between the control variables.

Fig. 8 shows the cost of purchasing electricity from the upstream network after the reconfiguration. As it is clear from Fig. 8, the maximum price of the total purchase of electricity has reached about 0.07 dollars. This means that the lowest cost that we have to spend in 24 hours to buy electricity from

Table 2. The degree of convergence of the objective function by using different optimization algorithms

	GWO	PSO	TLBO
The number of the convergence of the algorithm	-180.1614	-453.7	-450.8679

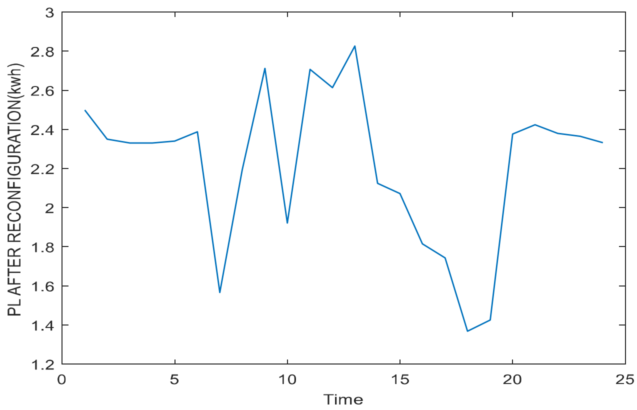

Fig. 9. Losses of lines after reconfiguration

the upstream network is around 12 o'clock and this cost is equivalent to 0.07 dollars. Due to the smallness of this value compared to the cost of power received from the upstream network between 1 am to 5 am and 8 pm to 24 pm, which solar panels are not present in the system, the value of 0.07 is not clear in the Fig. 8 and is shown as almost zero.

Fig. 9 also shows the amount of power loss in the system lines after the reconfiguration. After the reeconfiguration, the maximum loss of the system is about 2.88 kW, which is clear that the system loss has decreased significantly. In fact, the highest amount of losses in the power system in this case is around 18:00 and the losses of the power system in this hour are about 2.88 kilowatts.

By comparing the results of the convergence of the algorithms in table 2, it is clear that the performance of the particle swarm algorithm was better than the gray wolf algorithms and the algorithm based on learning and training, since the objective function has been optimized in a better way.

5- Conclusion

In part 4, a system was considered, which was a radial system with 33 buses. The goal was minimizing voltage deviations, losses, maximizing the host capacity, and minimizing the purchase price of electricity from the upstream network by carrying out the proper adjustment and coordination between the SVC fire angle and the output reactive power of the solar panels. As it can be seen from the results introduced in part 4, we achieved these goals in the best way and it was found that the reconfiguration and effective coordination between the control variables can effectively help the users of the power system to improve the use of the power system.

References

[1] R. Torquato, D. Salles, C. O. Pereira, P. C. M. Meira, and W. Freitas, "A comprehensive assessment of PV hosting capacity on low-voltage distribution systems," IEEE Transactions on Power Delivery, vol. 33, no. 2, pp. 1002-1012, 2018.

[2] H. Al-Saadi, R. Zivanovic, and S. F. Al-Sarawi, "Probabilistic hosting capacity for active distribution networks," IEEE Transactions on Industrial Informatics, vol. 13, no. 5, pp. 2519-2532, 2017.

[3] F. Ding and B. Mather, "On distributed PV hosting capacity estimation, sensitivity study, and improvement," IEEE Transactions on Sustainable Energy, vol. 8, no. 3, pp. 1010-1020, 2016.

[4] X. Chen, W. Wu, and B. Zhang, "Robust capacity assessment of distributed generation in unbalanced distribution networks incorporating ANM techniques," IEEE Transactions on Sustainable Energy, vol. 9, no. 2, pp. 651-663, 2017.

[5] F. Sun, J. Ma, M. Yu, and W. Wei, "Optimized two-time scale robust dispatching method for the multi-terminal soft open point in unbalanced active distribution networks," IEEE Transactions on Sustainable Energy, vol. 12, no. 1, pp. 587-598, 2020.

[6] J. M. Bloemink and T. C. Green, "Increasing photovoltaic penetration with local energy storage and soft normally-open points," in 2011 IEEE power and energy society general meeting, 2011: IEEE, pp. 1-8.

[7] M. Shafie-Khah, P. Siano, D. Z. Fitiwi, N. Mahmoudi, and J. P. Catalao, "An innovative two-level model for electric vehicle parking lots in distribution systems with renewable energy," IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1506-1520, 2017.

[8] S. Zhang, Y. Fang, H. Zhang, H. Cheng, and X. Wang, "Maximum Hosting Capacity of Photovoltaic Generation in SOP-based Power Distribution Network Integrated with Electric Vehicles," IEEE Transactions on Industrial Informatics, 2022.

[9] J. M. Home-Ortiz, L. H. Macedo, R. Vargas, R. Romero, J. R. S. Mantovani, and J. P. Catalão, "Increasing the RES hosting capacity in distribution systems through reconfiguration with closed-loop operation and voltage control," in 2021 International Conference on Smart Energy Systems and Technologies (SEST), 2021: IEEE,

pp. 1-6.

[10] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: harmony search," simulation, vol. 76, no. 2, pp. 60-68, 2001.

[11] J. H. Holland, "Genetic algorithms," Scientific american, vol. 267, no. 1, pp. 66-73, 1992.

[12] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proceedings of ICNN'95-international conference on neural networks, 1995, vol. 4: IEEE, pp. 1942-1948.

[13] R. Storn and K. Price, "Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces," Journal of global optimization, vol. 11, no. 4, pp. 341-359, 1997.

[14] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," Advances in engineering software, vol. 69, pp. 46-61, 2014.

[15] E. Emary, H. M. Zawbaa, and A. E. Hassanien, "Binary grey wolf optimization approaches for feature selection," Neurocomputing, vol. 172, pp. 371-381, 2016.

[16] L. M. Rios and N. V. Sahinidis, "Derivative-free optimization: a review of algorithms and comparison of software implementations," Journal of Global Optimization, vol. 56, no. 3, pp. 1247-1293, 2013.

[17] Y. P. Agalgaonkar, B. C. Pal, and R. A. Jabr, "Distribution voltage control considering the impact of PV generation on tap changers and autonomous regulators," IEEE Transactions on Power Systems, vol. 29, no. 1, pp. 182-192, 2013.

[18] Y. Zhu and K. Tomsovic, "Optimal distribution power flow for systems with distributed energy resources," International Journal of Electrical Power & Energy Systems, vol. 29, no. 3, pp. 260-267, 2007.

[19] K. Y. Lee and M. A. El-Sharkawi, Modern heuristic optimization techniques: theory and applications to power systems. John Wiley & Sons, 2008.

[20] S. Mohanty, B. Subudhi, and P. K. Ray, "A new MPPT design using grey wolf optimization technique for photovoltaic system under partial shading conditions," IEEE Transactions on Sustainable Energy, vol. 7, no. 1, pp. 181-188, 2015.

[21] Z. M. Yasin, N. A. Salim, and H. Mohamad, "Optimal Location and Sizing of Wind-Turbine Generation using Grey Wolf Optimizer," in 2022 IEEE International Conference in Power Engineering Application (ICPEA), 2022: IEEE, pp. 1-6.

[22] M. Sodani, H. H. Aly, and T. A. Little, "Optimal Planning of Distributed Generation Using Improved Grey Wolf Optimizer and Combined Power loss Sensitivity," in 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2021: IEEE, pp. 1-6.

[23] B. Venkateswararao and G. Balasubramanian, "Whale Optimization Algorithm based Optimal Power Flow: In View of Power Losses, Voltage Stability and Emission," in 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), 2021: IEEE, pp. 1-6.

[24] Z. ZHANG, H. Li, and W. Shuang, "Reconfiguration Strategy of Multi-objective Optimal Dispatching with Distributed Generation," in 2020 10th International Conference on Power and Energy Systems (ICPES), 2020: IEEE, pp. 99-103.

[25] M. Mahdavi and R. Romero, "Reconfiguration of radial distribution systems: An efficient mathematical model," IEEE Latin America Transactions, vol. 19, no. 7, pp. 1172-1181, 2021.

[26] A. Noori, Y. Zhang, N. Nouri, and M. Hajivand, "Multi-objective optimal placement and sizing of distribution static compensator in radial distribution networks with variable residential, commercial and industrial demands considering reliability," IEEE Access, vol. 9, pp. 46911-46926, 2021.

[27] C. Ghinea, M. Eremia, D. O. Sidea, and L. Toma, "Optimal location of a PV system using grey wolf optimizer and operation analysis," in 2021 9th International Conference on Modern Power Systems (MPS), 2021: IEEE, pp. 1-6.

[28] R. Rajaram, K. S. Kumar, and N. Rajasekar, "Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with Distributed Generation (DG)," Energy Reports, vol. 1, pp. 116-122, 2015.

[29] O. Ceylan, G. Liu, and K. Tomsovic, "Coordinated distribution network control of tap changer transformers, capacitors and PV inverters," Electrical Engineering, vol. 100, no. 2, pp. 1133-1146, 2018.

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